Automatic Detection of Cardiovascular Abnormalities in ECG Images: CNN and MobileNet

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Abstract: Cardiovascular diseases are becoming a leading cause of death worldwide. Detection of irregular heart activities like arrhythmia and heart attacks are critical for timely treatment. Automation in detecting cardiovascular abnormalities is essential for providing timely diagnosis, especially in resource-limited settings where trained medical professionals may be scarce. The paper aims to detect cardiovascular abnormality in ECG images automatically using deep learning techniques. It uses a Convolutional Neural Network(CNN) and MobileNet for efficient and lightweight processing. The MobileNet model outperforms the CNN model, demonstrating superior accuracy, precision and recall. The results show the potential of deep learning models in enhancing the accuracy and automation of cardiovascular abnormality detection through ECG analysis. By automating ECG interpretation, it enables early detection of abnormalities, reduces diagnostic delays, and improves patient care, particularly in resource-constrained settings.

1 INTRODUCTION

Electrocardiogram (ECG) imaging is an essential diagnostic tool used in cardiology to measure heart activity. It monitors the electrical signals of the heart and is basically used for detecting various abnormalities in heart activities like arrhythmia and myocardial infractions. Abnormalities in ECG images often indicate severe cardiovascular conditions that require immediate medical attention. Delayed diagnosis can lead to critical consequences for patients. Automated abnormality detection plays a crucial role in addressing this issue by enabling quick and accurate analysis of ECG data, facilitating early and effective treatment.

Cardiovascular diseases are the leading cause of death globally, taking an estimated 17.9 million lives each year. According to (World Health Organization, 2015), in 2000, around 14 million people died from cardiovascular diseases globally, while in 2019, it reached close to 18 million. The emerged need for improved healthcare systems is more important than ever, particularly as cardiovascular diseases remain to be the leading cause of death worldwide. ECG imaging is at forefront of heart care monitoring due to its ability to capture the critical data of the heart.

(Agarwal et al., 2024) presents a novel approach for detecting abnormalities in ECG images by utilizing a MobileNet based CNN autoencoder. The lightweight architecture is designed for efficient processing, making it ideal for real-time applications and devices with limited computational resources. The autoencoder learns compact representations of ECG images during the encoding phase and reconstructs them during decoding, allowing the system to identify abnormalities based on discrepancies between the original and reconstructed images. By leveraging MobileNet's efficiency and the autoencoder's capability to highlight subtle deviations, the method achieves high diagnostic accuracy. The study demonstrates the potential of this approach for improving anomaly detection in ECG images, ensuring reliability and scalability across different datasets and clinical scenarios.
The MobileNet50 CNN autoencoder method for ECG anomaly detection has several potential drawbacks. It faces challenge with overfitting on limited or biased datasets, reducing generalizability across diverse populations. Handling noisy ECG signals, common in real-world scenarios, also degrade performance. The

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method's reliance on a complex deep learning architecture introduces latency and impacting real-time applications. Additionally, without thorough comparison to simpler techniques or clinical validation, its real-world efficacy remains uncertain. Addressing these issues with robust datasets enhance its practical applicability. The deep-learning models for MI detection and QRS complex detection face many challenges. Deep learning techniques used like 1D CNNs and hybrids of CNN-LSTM are limited by high computational resources and data dependency. Image-based methods and low-quality signal processing majorly have difficulties with noise reduction, feature extraction etc. The models perform better in some environments but struggle with over-fitting which impacts the real-world applications. Enhanced machine learning and deep learning algorithms need thorough validation in clinical settings.

The challenges observed in the problem space include data availability and format, where the open-access datasets for ECG images are limited. ECG data is usually recorded on paper in clinical settings which makes it difficult to digitize, store and analyze the data. ECG images usually consists of text-annotations, grid lines and other background elements that often interfere with the image extraction. The other challenges include model performance and validation, where achieving high sensitivity is crucial as false negatives in MI detection can have serious health consequences. These challenges highlight the importance of using reliable image processing and machine learning methods to accurately identify heart diseases using ECG images.

The present study introduces an advanced abnormality detection model that utilizes CNNs for accurate and reliable classification. The model is specifically designed to handle ECG image data, ensuring that it undergoes thorough preprocessing to improve input quality. By leveraging the preprocessing steps, the model enhances the consistency and quality of the ECG image data. Furthermore, the CNN-based architecture excels in extracting meaningful and relevant features from the processed ECG images, enabling efficient classification of abnormalities. This approach aims to address challenges in medical diagnostics by providing a robust and precise solution for ECG analysis.

The paper is organized as follows. Section 2 provides a brief review of the literature survey on the recent works. Section 3 contains the problem statement, background and provides proposed methodology. Section 4 discusses the implementation details along with results and discussions. Finally, the paper concludes in Section 5.

2 RELATED WORKS

The detection of ECG peaks has seen exceptional progress with the application of advanced image processing techniques and deep learning algorithms. This survey explores a wide range of methods proposed by researchers for accurate and efficient detection of ECG features which enables the detection of arrhythmia and other cardiac conditions.

(Sane et al., 2021) developed a computerized method for detecting Myocardial Infarction(MI) by using a dataset containing 12-lead ECG images. They included a two-step approach which involved image processing to extract ECG signals from the images, followed by a one-dimensional CNN to classify MI. The model is validated on the PTB diagnostic database. This method avoids the need for manual computation and handcrafted features. The advantage of this model is that it is adaptable to various datasets and provides real-time assessment, which makes it well-suited for critical health conditions. However,the limitation lies in the challenge of extracting signals from ECG images and the lack of open access to ECG image datasets.

(Zhou et al., 2020) introduced a novel deep-learning algorithm for the real-time prediction of R-peaks in ECG signals using a combined model of CNN and LSTM network. The designed strategy is to predict the next R-peak by computing the variability of previous ECG intervals which indicate the potential future health problems like depression, anxiety, asthma and sudden infant death. It also proves to be a strong indicator for the onset of myocardial infractions. The model is validated on MIT-BIH arrhythmia dataset and the combined model outperforms the standalone models like CNN or LSTM by combining their strengths. CNN has been used for filtering noise and extracting visual pattern, LSTM for handling temporal dynamics in ECG signals. The advantage of the model includes its ability to perform real-time monitoring. However, the accessibility of high-quality ECG data and computational resources are the key-issues.

(Yuen et al., 2019) developed a innovative CNN-LSTM model for identifying QRS complexes in noisy ECG signals. In this approach, CNN is used to extract features, LSTM identifies the QRS complex timings, and a multi-layer perceptron makes the final predictions. The model performs well in scenarios where the training and testing datasets have data from different patients. It is tested using the MIT-BIH dataset and evaluated based on metrics like precision, recall, and F1 score. Advantages of this approach include adaptability to noisy signals which makes it suitable to generalize on unseen patient data.

(Cai and Hu, 2020) introduced two deep learning models for QRS complex detection in ECG signals: a CNN and a hybrid Convolutional Recurrent Neural Network(CRNN). The CNN is fundamentally conposed of convolutional blocks and Sqeeze-and-Exitation networks, while the CRN combines both convolutional and recurrent layers to improve feature extraction and temporal dependency learning. The model is evaluated on four open access ECG datasets. Advantages of this model involves its noise resistance and high accuracy, however it faces issues such as over-fitting, computational complexity which limits their effectiveness in real-time applications.

(Zahid et al., 2022) created a reliable system to detect R-peaks in low-quality Holter ECG signals. It uses a 1D CNN combined with a verification model to reduce false alarms. The approach includes a encoder-decoder structure that generates a 1D segmentation map for precise localization of R-peaks from ECG inputs. The model is tested on China Physiological Signal Challenge(CPSC) and MIT-BIH Arrhythmia database, achieving a excellent performance on F1 score on CPSC database while showing better results on MIT-BIH database. The advantages of this approach lies in the adaptability to low-quality signals and its generalization across different datasets, which makes it suitable for real-time applications. However,the issue of over-fitting remains as a challenge, particularly in variable ECG environments.

(Das, 2024) proposed a comprehensive system for blood pressure prediction using three machine learning algorithms: Support Vector Classifier (SVC), Random Forest Classifier, and Naive Bayes Classifier. The approach is tested on a dataset consisting of 3000 image samples, of which 2005 represented cases of high blood pressure and 495 represented normal blood pressure. The strength of the model lies in the synergistic use of multiple algorithms, which significantly enhances the accuracy and reliability of predictions by leveraging the strengths of each method. SVC effectively handles the separation of complex data, Random Forest contributes robustness through ensemble learning, and Naive Bayes adds simplicity and speed to the classification process. One major drawback is the increased computational complexity, which arises from training multiple algorithms and integrating their outputs. Efficiently handling large datasets remains challenging due to high memory usage and processing time.

(Yang et al., 2021) proposed a hybrid deep learning model for non-invasive, cuff-less blood pressure estimation. The study focuses on using raw ECG images directly as input for deep learning models. Two types of experiments are caried out. In the first, physical characteristics and features from the ECG signals are extracted and used with traditional ML techniques like SVR, LASSO, Ridge regression, KNN, Multiple Linear Regression, and AdaBoost. In the second, DL models such as CNNs, LSTMs, and fully connected networks are applied for testing and analysis of model. The advantage of the model is its ability to automatically extract features from raw PPG and ECG signals which reduces the complexity of use for users. However, a disadvantage is the model's reliance on insufficient data for optimal performance. Table 1 illustrates recent 2024 literature surveys for cardiovascular diseases detection in ECG Images.

In conclusion, the literature survey provides a comprehensive overview of research on abnormalities in ECG images, highlighting a wide range of studies that identify key trends and systematic methodologies. By addressing the existing gaps in this domain, the study aims to contribute significantly to the advancement of accurate and efficient detection of cardiovascular abnormalities.

3 PROPOSED METHODOLOGY

The study aims on detecting abnormalities in ECG images by utilizing advanced and enhanced deep learning techniques to identify irregular heart activities such as arrhythmia and MI. Consider a patient experiencing chest pain. An ECG is conducted, and the image is analyzed for any signs of MI or other irregular heart conditions. Currently, the analysis is performed manually by trained professionals. However this can lead to delays and many inconsistencies. An automated model quickly detects whether the ECG contains any abnormalities which takes less usage of time and treatment decisions can be taken on time.

The objectives are as follows :

- To preprocess the data by cleaning it to improve the image quality of ECG images for better performance of the model.
- To design and implement robust deep learning models for accurate detection and classification of abnormalities in ECG signals.
- To assess the developed model's performance by using the evaluation metrics.

Quality of ECG images is assumed that the ECG images provided are of acceptable resolution and sufficient quality for processing is present. The ECG images are assumed to have consistent dimensions

Table 1: Literature Surveys for Cardiovascular Diseases Detection.

Year	**Paper Title**	**Dataset**	**Approach**	**Accuracy**	**Precision**	**Recall**	**F-score**	**Gaps identified**
2024	Detection of Cardiovascular Disease Using ECG images (Jessy et al., 2024)	ECG dataset collected from hospitals	SVM, K-NN, DT, RF, Naive Bayes	98.23%	98.31%	97.50%	97.90%	Limited generalizability; focus on classification only
2024	Interpreting Deviant Heart Patterns: MobileNet CNN Autoencoder (Agarwal et al., 2024)	ECG images dataset with anomalies	MobileNet (CNN)	76.93%	55.23%	70.00%	61.63%	Low accuracy and not effective on larger ECG datasets
2022	Pan-Tompkins++: A Robust Approach to Detect R peaks in ECG Signals (Imtiaz and Khan, 2022)	MIT-BIH Arrhythmia, European ST-T, PhysioNET PTB, Atrial Fibrillation dataset	CNN, CRNN	97.49%	95.89%	96.00%	95.94%	High processing demands
2022	Energy Efficient Compression Algorithm of ECG Signals (Fathi et al., 2022)	Real-time ECG images dataset	Krawtchouk and AALO algorithm	92.00%	91.00%	90.00%	90.50%	Lack of anomaly detection capabilities
2022	Intelligent System for ECG Classification Using CNN (Hammad and Abdulbaqi, 2022)	Publicly available ECG dataset	1D CNN	90.00%	88.00%	87.00%	87.50%	Limited in handling diverse ECG signal variations

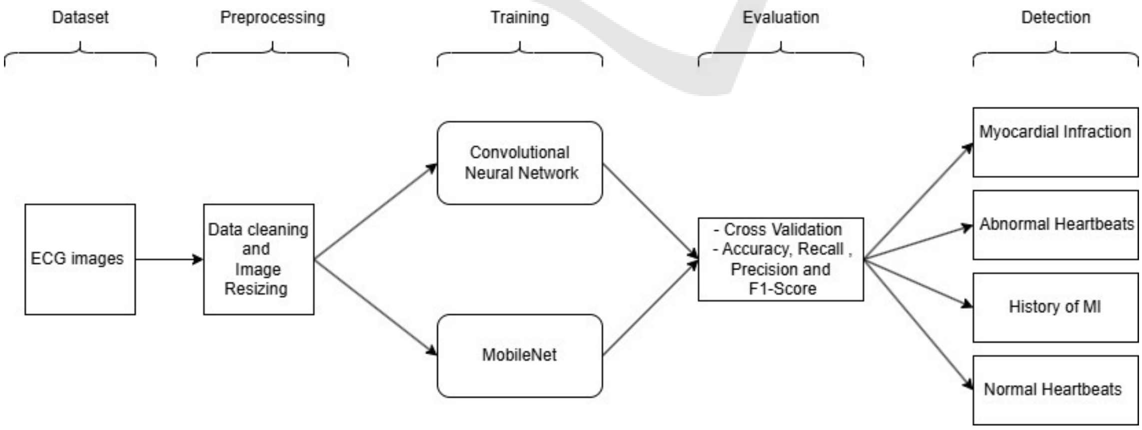

Figure 1: Proposed Methodology for Cardiovascular Abnormality Detection.

after pre-processing, making them compatible with a CNN model. It is assumed that a sufficient amount of labeled ECG image data is provided for testing and training.

The proposed solution utilizes deep learning models, specifically CNN and MobileNet, to automate the detection of ECG signal abnormalities, offering a fast, accurate, and reliable diagnostic tool for cardiovascular diseases. The methodology begins by preprocessing ECG signals to ensure consistency across ECG samples. CNN extracts critical temporal and spectral features, such as P and T waves and QRS complexes, which are vital for identifying cardiac conditions. Its convolutional layers capture complex patterns, pooling layers reduce dimensionality while preserving essential information. The fully connected layers classify signals into normal or abnormal categories. Complementing this, MobileNet a lightweight architecture, is fine-tuned on the ECG dataset for efficient real-time analysis, using depthwise separable convolutions to optimize feature extraction with minimal computational overhead. A global average pooling layer and customized dense layers adapt MobileNet for ECG classification. Both models are trained on the same dataset with early stopping to avoid overfitting and ensure optimal performance. Comprehensive evaluation metrics, including accuracy, precision, recall, F1-score, and confusion matrix, are used to assess their effectiveness. The framework uses CNN's robustness and MobileNet's efficiency to deliver a scalable and accessible solution for ECG analysis.

The schematic diagram illustrating the proposed methodology is depicted in Figure 1. Initially, ECG images are drawn from the dataset consists of labeled samples of ECG signals. Preprocessing steps such as resizing the images to a standard dimension and normalizing pixel intensity values are performed to ensure data consistency and quality. These steps aim to enhance the clarity of the ECG images, which is crucial for accurate feature extraction. The preprocessed ECG images are then trained using CNN and MobileNet models. The CNN architecture incorporates convolutional layers that use filters to extract local features, pooling layers to reduce spatial dimensions, and fully connected layers to predict the class labels by analyzing the acquired features. Activation function, such as ReLU, introduce non-linearity, enabling the network to learn complex patterns and relationships in ECG images. CNNs excel in automatically extracting hierarchical representations of features from ECG images, which facilitates effective classification of normal and abnormal ECG. Similarly, the MobileNet model is employed to efficiently analyze ECG images with reduced computational complexity. It uses depth-wise separable convolutions to optimize the feature extraction process while maintaining high classification accuracy. This makes it particularly suitable for real-time applications in clinical settings. Finally, the trained models are evaluated using performance metrics such as accuracy, precision and recall to validate their effectiveness. The evaluated models are then used to detect abnormalities in new ECG images, classifying them into normal or abnormal categories. The results are visualized to provide clinicians with interpretable insights, aiding in decision-making for cardiac health monitoring and diagnosis.

4 RESULTS AND DISCUSSION

The experiments are conducted on a machine with an Intel(R) core(TM) i3-7020U processor operating at 2.30 Ghz equipped with 4 GB RAM and running on Windows 10. The implementation is carried out using Python, with Tensorflow and keras serving as the primary libraries for developing the deep learning models. Additional libraries such as NumPy and Pandas are used for efficient data manipulation and analysis.

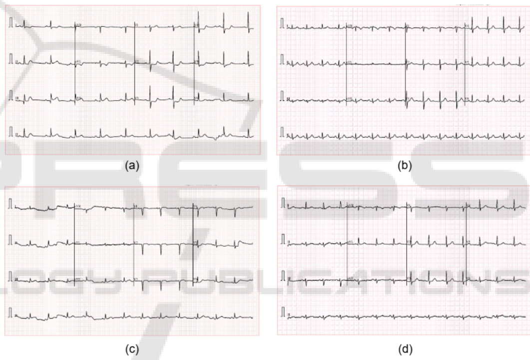

Figure 2: Sample Images: (a) Myocardial Infraction, (b) Abnormal Heartbeats, (c) History of MI, (d) Normal Heartbeats.

The dataset used in this study is sourced from mendeley data and comprises a collection of 12-lead ECG images, categorized into various classes such as normal, myocardial infarction, abnormal heartbeat, and history of myocardial infarction. The Figure 2 shows the sample images. The proposed method is focused on the targeted analysis of ECG images, specifically concentrating on identifying abnormalities indicative of cardiac conditions. The entire dataset consists of 1,377 ECG images, divided into training and testing subsets. The training dataset comprises 929 samples, used to train the model by extracting and learning features, essential for distinguishing normal from abnormal ECG images. The testing dataset includes 448 samples, reserved for evaluating the model's performance and generalization capability. The dataset ensures a balanced representation of normal and abnormal ECG images to support effective classification and robust model performance. In the study, a comprehensive approach is applied for the detection and classifications of ECG peaks, aiming to distinguish between normal and abnormal patterns. The approach focuses on automating the ECG images, which is critical in diagnosing cardiac conditions. Two deep learning models, a custom CNN and MobileNet architectures are implemented to perform the classification task.

The first step in this study involves designing and training a custom CNN to classify the ECG images into four predefined categories. The architecture consisted of an input layer accepting images of size(100, 100, 3) followed by three CNN filter sizes of 32, 64 and 128. These layers are accompanied by ReLU activation functions and max-pooling layers to reduce the spatial dimensions of the feature maps. The final layers include dense layer with 128 neurons using ReLU activation function. The output layer consists of four neurons employing the softmax function for multi-class classification, where the four neurons indicate myocardial infarction, abnormal heartbeats, history of myocardial infarction, and normal heartbeats. The model is trained over 20 epochs. The performance of the CNN model is remarkable achieving a test accuracy of 90.98% and a minimal test loss of 0.029. It is observed that, as epochs increase, accuracy increases and loss decreases.

The next step employs MobileNet, a lightweight and efficient CNN architecture, for image classification. The approach is particularly effective for medical imaging tasks due to its computational efficiency and high accuracy. The base MobileNet model is pre-trained on ImageNet data but initialized with custom weights in this implementation. The fully connected top layers are removed to allow fine-tuning for type specific task. A custom classifier is added, which includes a global average pooling layer followed by two dense layers, one with 128 neurons using ReLU activation and the other with softmax activation to output probabilities for multiple classes. The MobileNet model is compiled using the Adam optimizer with a learning rate of 0.0001. The categorical cross entropy loss function is employed as the dataset is multi-class in nature. Accuracy is chosen as the evaluation metric. To prevent overfitting and ensure early convergence, an early stopping callback is applied monitoring validation loss and restoring the best weights if no improvement is observed after given consecutive epochs. Training the model occurred over a minimum of 50 epochs, although the early stopping criterion terminated training early upon validation loss stabilization. The training results showed a progressive improvement in accuracy and reduction in loss over epochs. The final evaluation gives test accuracy of approximately 91.73% and a test loss of 0.445. Figure 3, shows the accuracy of the MobileNet model and it is observed that, as epochs increase, accuracy also increases. Figure 4, shows the loss of the MobileNet model and it shows that, as epochs increase, loss decreases.

The confusion matrix in Figure 8 shows the performance of the model on the ECG dataset. It is observed that the model accurately classifies the majority of normal and abnormal heartbeats, as well as MI and patients with MI history. However, there are a few misclassifications, with a small number of abnormal heartbeats being misclassified as normal, and vice versa. Overall, the loss is minimal, indicating that the model performs well in detecting and classifying ECG images. These highlight the capability of the MobileNet model in effectively classifying images. Compared to traditional CNN's, MobileNet offered a significant advantage in terms of reduced computation and memory requirements while maintaining high accuracy. The efficiency is achieved by employing depth wise separable convolutions which reduces the number of parameters and computational cost. The inclusion of dropout layers and global average pooling further reduced overfitting while enabling robust feature extraction. In summary, the MobileNet-based models successfully demonstrated high accuracy and efficiency, underlining its potential for real-world applications in detecting abnormalities in ECG images.

The Table 2 clearly highlights the superiority of MobileNet over CNN in detecting ECG abnormalities. MobileNet achieves a higher accuracy of 91.73% compared to CNN's 90%, and excels with an F1-Score of 96% versus CNN's 95%. MobileNet also outperforms CNN in precision and recall, achieving 96% for both, compared to CNN's 95% precision and 94% recall, further emphasizing its effectiveness in minimizing false positives and negatives. When compared to other existing methods, such as the approach proposed by (Agarwal et al., 2024), which focuses on ECG anomaly detection using MobileNet50 CNN autoencoder, and the method by Sane et al. (Cai and Hu, 2020), which centers on detecting myocardial infarction from 12-lead ECG images, MobileNet demonstrates superior performance. The methods in (Agarwal et al., 2024) and (Cai and Hu, 2020) report lower accuracies and F1-Scores, with precision and recall metrics that fall short of MobileNet's consistent 96% values. Overall, MobileNet outperforms CNN and existing methods in accuracy, precision, recall, and F1-Score, solidifying its position as a highly effective model for detecting abnormalities in ECG images.

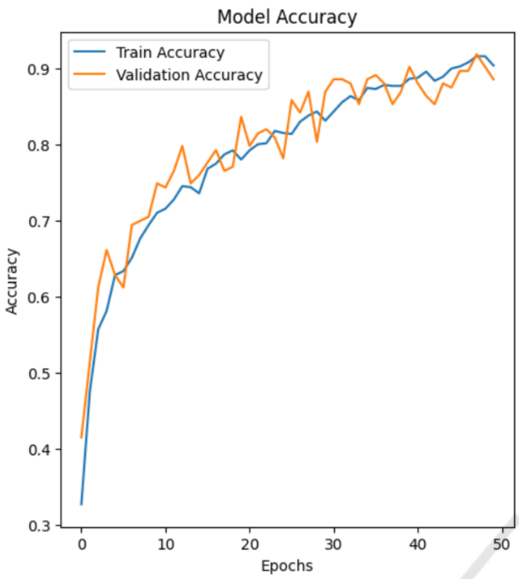

Figure 3: Accuracy of MobileNet model.

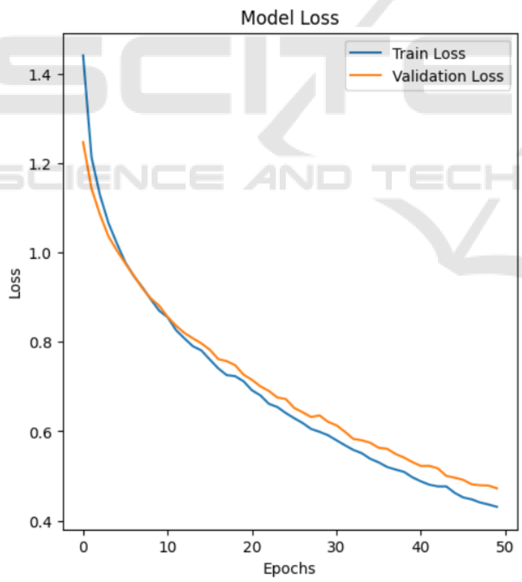

Figure 4: Loss of MobileNet model.

5 CONCLUSIONS

The study utilizes advanced DL models: CNN and MobileNet, for classification of ECG images into four classes to detect abnormalities. The CNN model, featuring three convolutional layers to extract key patterns like P waves, QRS complexes, and T waves, is followed by dense layers for classification. Trained over 20 epochs, it achieved a test accuracy of 90.98%, highlighting its efficacy in diagnosing cardiovascular conditions. MobileNet, a lightweight and pre-trained DL architecture, is also employed for this study. Known for its computational efficiency, MobileNet demonstrated robust performance by leveraging its depthwise separable convolutional layers to extract features efficiently. Fine-tuned for the ECG classification task, MobileNet achieved a test accuracy of 91.73%, proving its adaptability and effectiveness in handling medical image data. MobileNet's lightweight design and faster inference time make it highly suitable for real-time applications, such as portable ECG monitoring devices and telemedicine platforms. Among the two approaches, MobileNet emerges as the more practical solution for real-world deployment due to its efficient architecture and scalability. However, the MobileNet model demonstrates superior accuracy, showcasing its capability for detailed and precise classification, which is particularly beneficial in controlled or research settings. Future advancements aim to improve ECG analysis by developing more accurate and efficient tools for detecting cardiac anomalies. These innovations will leverage AI and real-time monitoring to enable early diagnosis and better outcomes. However, their applicability may be limited to ECG-specific data, requiring complementary tools for broader diagnostic needs.

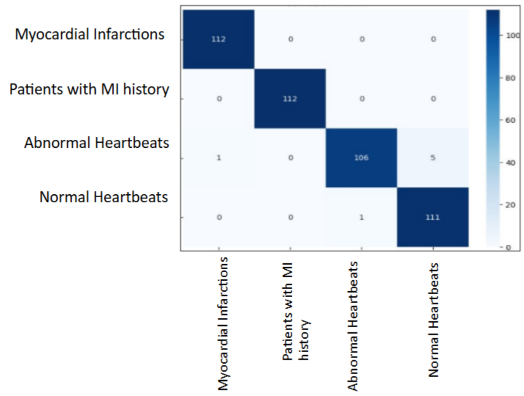

Figure 5: Confusion Matrix of MobileNet.

Table 2: Quantitative Comparison of CNN and MobileNet.

Performance parameters	(Sane et al., 2021)	(Agarwal et al., 2024)	CNN	MobileNet
Accuracy	86.21%	76.93%	90%	91.73%
Precision	91.30%	55.23%	95%	96%
Recall	85%	70%	94%	96%
F1-Score	88.05%	61.63%	95%	96%

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